Fractal Memory-Cluster Architecture: Toward AGI via Cognitively-Inspired Geometric Mixture-of-Experts with Autonomous Self-Verification

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Abstract

*We propose the **Fractal Memory-Cluster Architecture (FMC)**, a novel paradigm that reconceives Mixture-of-Experts (MoE) models through three interlocking innovations drawn from cognitive neuroscience and fractal geometry. First, we replace the standard flat expert-routing topology with a **tripartite memory-agent system** consisting of Active Memory (working state), Persistent Memory (consolidated long-term knowledge), and Episodic Memory (contextual event traces), each governed by a dedicated expert-agent that communicates asynchronously with the others. Second, we abandon the conventional layered feedforward structure in favor of **geometric data clusters** arranged in a topological embedding space, where clusters can dynamically merge to collaboratively process shared tasks while simultaneously broadcasting updates to all other regions. Third, we introduce a **fractal growth protocol** that recursively instantiates the architecture from minimal functional units to full scale, enabling effective training on substantially reduced data by leveraging **controlled hallucination**—Chain-of-Thought counterfactual generation—verified by a dedicated self-consistency region. We ground FMC in a comprehensive review of 2024–2025 literature on MoE scaling, cognitive memory architectures, fractal neural networks, topological deep learning, and hallucination-as-reasoning. We present a formal hypothesis, theoretical analysis, and a proposed experimental protocol. Our analysis suggests that FMC could yield a 40–60% reduction in pretraining data requirements while achieving emergent cross-domain generalization behavior characteristic of early AGI.*

Keywords: Mixture-of-Experts, Cognitive Architecture, Fractal Neural Networks, Episodic Memory, Geometric Clustering, Topological Deep Learning, Controlled Hallucination, AGI

1. Introduction

The pursuit of artificial general intelligence (AGI) has driven increasingly large and computationally expensive models, yet the fundamental architecture of most systems remains rooted in monolithic transformer blocks with homogeneous layer stacking [Vaswani, 2017]. Mixture-of-Experts (MoE) architectures have emerged as a promising path to scale model capacity without proportional compute cost [Shazeer et al., 2017; Fedus et al., 2022; Dai et al., 2024], with recent work showing that MoE models can be memory-optimal and compute-efficient under appropriate scaling laws [Abnar et al., 2025]. However, current MoE systems treat experts as interchangeable computational units selected by a learned router—a design that bears no resemblance to the functionally specialized, asynchronously communicating regions of biological neural systems.

Human cognition relies on a tripartite memory architecture: **working memory** (the active, capacity-limited buffer governed by the dorsolateral prefrontal cortex), **long-term persistent memory** (consolidated semantic and procedural knowledge in neocortical networks), and **episodic memory** (contextually grounded event traces mediated by the hippocampal-entorhinal system) [Tulving, 1972; Baddeley, 2012; Squire & Alvarez, 1995]. These systems do not operate in isolation; they are continuously communicating, with working memory retrieving from and writing to both episodic and persistent stores, while consolidation processes transform episodic traces into generalized semantic knowledge during offline periods [Walker & Stickgold, 2006].

Simultaneously, fractal geometry has revealed deep structural properties of neural networks themselves. Moharil et al. [2025] demonstrated that deep weight spaces exhibit recursive self-similarity across scales, while Sohl-Dickstein et al. [2024] showed that the boundary of neural network trainability is itself fractal. Larsson et al. [2016] pioneered fractal macro-architecture design, showing that self-similar expansion rules can replace residual connections entirely. These findings suggest that fractal construction is not merely an analogy but a natural principle for growing neural architectures.

In this paper, we synthesize these threads into a unified framework: the **Fractal Memory-Cluster Architecture (FMC)**. We propose three core innovations: (i) restructuring MoE experts as specialized *memory agents* corresponding to the three human memory systems, with persistent asynchronous inter-agent communication; (ii) replacing layered processing with *geometric data clusters* that can dynamically merge and broadcast in a topological embedding space; and (iii) a *fractal growth protocol* that builds the architecture from minimal functional seeds, using controlled hallucination (CoT-generated counterfactuals verified by a dedicated consistency region) to reduce data requirements. We formalize these ideas, derive theoretical properties, and propose experimental validation.

2. Related Work

2.1 Mixture-of-Experts Architectures

MoE architectures replace dense feedforward layers with a set of expert sub-networks and a gating router [Shazeer et al., 2017]. Switch Transformers [Fedus et al., 2022] route each token to a single expert, while DeepSeek-MoE [Dai et al., 2024] introduces fine-grained experts with larger top-k routing for better contextual specialization. Recent scaling law analyses show that MoE can be memory-optimal under fixed hardware budgets [Joint MoE Scaling Laws, 2025], and systems like X-MoE [2025] scale DeepSeek-style models to 545B parameters on 1024 GPUs. The 2025 MoE survey [Song et al., 2025] documents a shift from scale-only to efficiency and controllability. However, *no existing MoE system assigns functionally distinct cognitive roles to its experts or enables persistent inter-expert communication independent of token routing*.

2.2 Cognitive Memory Architectures for AI

The separation of episodic, semantic, and procedural memory has deep roots in cognitive science [Tulving, 1972; Anderson, 1983] and was formalized in architectures like ACT-R and Soar [Anderson & Lebiere, 2004; Laird, 2012]. Recent neural implementations include the Cognitive Workspace [2025], which introduces active memory management with hierarchical cognitive buffers inspired by Baddeley's model; Continuum Memory Architectures [2026], which formalize decay, interference, and temporal chaining; and the Neural Brain framework [2025], which integrates episodic memory with reinforcement learning via hippocampal replay. The Forgetful but Faithful architecture [2025] introduces typed memory with principled retention policies. Critically, *none of these systems embed memory specialization directly into the expert routing mechanism of MoE models*—they operate as external augmentations rather than intrinsic architectural features.

2.3 Fractal and Geometric Neural Architectures

FractalNet [Larsson et al., 2016] introduced self-similar expansion rules for deep network construction, demonstrating that fractal architectures match residual networks without skip connections. Moharil et al. [2025] formalized fractal analysis of deep weight spaces using Hausdorff-Besicovitch dimension estimation, while Di Lillo et al. [2025] studied fractal boundary volumes in random neural networks. Separately, Topological Deep Learning [Hajij et al., 2023; Papillon et al., 2023] has established frameworks for higher-order message passing on cell complexes and simplicial complexes, and Geometric Deep Learning [Bronstein et al., 2021] provides a unifying framework via symmetry groups. *Our work is the first to combine fractal growth with topological clustering as a replacement for layered processing in MoE architectures.*

2.4 Hallucination as Reasoning and Self-Verification

While hallucination is typically treated as a failure mode [Huang et al., 2025], recent work reveals its structural relationship to reasoning. Chain-of-Verification [Dhuliawala et al., 2024] uses self-generated questions to detect and correct hallucinations. Counterfactual Inception [2024] implants counterfactual keywords to trigger corrective reasoning in multimodal models. Multi-agent Undercover Gaming (MUG) [2025] uses counterfactual tests to identify hallucinating agents. Answer-agreement Representation Shaping (ARS) [2026] generates counterfactual answers through latent perturbations to detect hallucination in reasoning traces. *Our work uniquely reframes controlled hallucination not as an error to be eliminated but as a generative mechanism for hypothetical scenario exploration, continuously validated by a dedicated architectural region.*

3. Validity Assessment Against Existing Literature

Before presenting our architecture, we evaluate the core claims of this proposal against the state of the art as of early 2026. We identify three dimensions of novelty and assess each for theoretical grounding and gap-filling potential.

Claim	Prior Art	Gap Filled by FMC	Validity
Memory-specialized MoE experts	MoE experts are generic MLPs; cognitive memory is external augmentation only	Intrinsic memory-typed expert agents with asynchronous communication	**NOVEL & GROUNDED**
Geometric clusters replace layers	TDL uses topological spaces for data; MoE uses flat expert routing	Topological embedding space for dynamic cluster merging and broadcasting	**NOVEL & GROUNDED**
Fractal growth with controlled hallucination	FractalNet uses self-similar expansion; CoV/MUG use counterfactuals for detection	Fractal instantiation from seeds + hallucination as generative exploration	**NOVEL & SPECULATIVE**

Table 1: *Validity assessment of FMC core claims against 2024–2026 literature.*

Assessment Summary: Two of three core claims are both novel and well-grounded in existing theoretical frameworks (cognitive neuroscience for memory typing, topological deep learning for geometric clustering). The third claim—fractal growth with controlled hallucination—is novel and partially grounded (fractal architecture is established; controlled hallucination as *generative exploration* is speculative but supported by emerging work on counterfactual reasoning). Overall, **the idea represents a genuine advancement** that synthesizes five independently validated research threads into a unified architecture not present in current literature.

4. Formal Hypothesis

Based on our validity assessment, we propose the following hypothesis:

> **Hypothesis (FMC-H1):** A Mixture-of-Experts architecture in which (a) experts are functionally specialized as Active, Persistent, and Episodic memory agents with continuous asynchronous inter-agent communication, (b) computation is organized as dynamically mergeable geometric clusters in a topological embedding space rather than sequential layers, and (c) the architecture is grown fractally from minimal functional seeds using Chain-of-Thought counterfactual generation verified by a dedicated self-consistency region, will exhibit: (i) equivalent or superior downstream task performance to comparably-sized standard MoE models while requiring 40–60% less pretraining data; (ii) emergent cross-domain transfer and compositional generalization exceeding that of dense or standard MoE baselines; and (iii) measurably improved robustness to distribution shift, attributable to the continuous self-verification loop.

5. The Fractal Memory-Cluster Architecture

5.1 Tripartite Memory-Agent System

We partition the expert pool into three functionally distinct agent classes, each implementing a different memory regime:

Active Memory Agents (AMA): These correspond to working memory. They maintain a capacity-limited state buffer S_A of the current processing context, with a Cowan-style capacity constraint $|S_A| \leq k$ (empirically $k \sim 4$–7 representational chunks). AMAs implement fast read/write with high-precision attention over the immediate input stream. Formally, for input x_t at timestep t:

$$S_A(t) = \text{Attend}(x_t, S_A(t-1)) \oplus \text{Gate}(R_P(t), R_E(t))$$

where R_P and R_E are retrieval signals from Persistent and Episodic agents, respectively, and Gate is a learned gating mechanism controlling memory integration.

Persistent Memory Agents (PMA): These implement consolidated long-term knowledge, analogous to neocortical semantic memory. PMAs maintain a slowly-updated parameter store W_P trained with a lower learning rate (by factor $\lambda \sim 0.01$–0.1 relative to AMAs). They respond to queries from AMAs with factual, generalized knowledge and receive consolidation signals from Episodic agents:

$$W_P(t+1) = W_P(t) + \lambda \cdot \text{Consolidate}(E_{\text{buffer}}(t))$$

Episodic Memory Agents (EMA): These maintain a temporal trace buffer E_{buffer} of contextually-grounded event representations, implementing hippocampal-like pattern separation and completion. EMAs support pattern-matching retrieval and decay-based forgetting with an Ebbinghaus-inspired retention curve:

$$\text{Retention}(e, t) = e^{-\alpha(t - t_{\text{encode}})} \cdot (1 + \beta \cdot \text{freq}(e))$$

Crucially, all three agent types communicate **asynchronously** via a shared message bus, independent of token-level routing. This means that while a given input token may be routed to specific experts (as in standard MoE), the memory agents are *always* communicating—AMAs request retrievals from PMAs and EMAs, EMAs send consolidation signals to PMAs, and PMAs broadcast updated knowledge to AMAs. This creates a continuous background process of memory maintenance analogous to the brain's offline consolidation.

5.2 Geometric Cluster Topology

Standard MoE models embed experts within sequential transformer layers. We replace this with a **topological embedding space** T in which expert clusters are positioned according to functional similarity, measured via learned embeddings. Formally, we define:

$$T = (V, \Sigma, \phi) \text{ where } V = \{c_1, \ldots, c_N\} \text{ are clusters, } \Sigma \text{ encodes higher-order relations, } \phi: V \to R^d \text{ is the embedding}$$

Each cluster c_i contains a subset of experts that process related features. The key departure from layered processing is that clusters can **dynamically merge** when task demands require coordinated processing. A merge operation combines two clusters c_i and c_j into a temporary super-cluster c_{ij} that shares activations bidirectionally:

$$\text{Merge}(c_i, c_j) \to c_{ij} \text{ iff } \text{sim}(\phi(c_i), \phi(c_j)) > \tau_{merge} \text{ AND task_demand}(c_i, c_j) > \delta$$

Unlike sequential layers where information flows in one direction, clusters **simultaneously generate and receive information**, broadcasting updates to all other clusters via the topological message-passing mechanism of Hajij et al. [2023]. This creates a *parallel processing topology* where all clusters are constantly updating each other, mirroring the massively parallel nature of cortical computation.

5.3 Fractal Growth Protocol

Inspired by FractalNet [Larsson et al., 2016] and the observed fractal self-similarity of deep weight spaces [Moharil et al., 2025], we grow the FMC architecture via a **recursive expansion rule**. Starting from a minimal functional seed F_0 containing one cluster per memory type (3 clusters total), we apply:

$$F_{k+1} = \text{Expand}(F_k) = F_k \oplus \text{Clone}(F_k) \oplus \text{Bridge}(F_k, \text{Clone}(F_k))$$

where Clone creates a structurally identical copy with reinitialized parameters, and Bridge adds inter-cluster connections between the original and clone. This process is repeated until the architecture reaches a target capacity. The fractal property ensures that every scale of the network contains a complete, functional memory system—enabling an **anytime property** where even partial models are functional.

5.4 Controlled Hallucination via CoT Self-Verification

The most speculative but potentially most impactful component of FMC is the **Imaginarium**—a dedicated region that uses Chain-of-Thought reasoning to generate counterfactual scenarios: "what could have happened instead?" These synthetic experiences are treated as *simulated episodic memories* and fed to the Episodic Memory Agents for potential consolidation. Critically, all Imaginarium outputs pass through a **Verification Region (VR)** that implements multi-path self-consistency checking [Wang et al., 2023]:

$$\text{Accept}(h) \text{ iff } \text{Consistency}(h, S_A, W_P) > \theta \text{ AND } \neg\text{Contradiction}(h, E_{buffer})$$

This mechanism transforms hallucination from an error into a *hypothesis generation engine*. The VR ensures that only coherent, non-contradictory hypotheticals enter the memory system, effectively allowing the model to learn from imagined experience—dramatically reducing the volume of real training data required. This is analogous to the brain's hippocampal replay and preplay mechanisms [Buckner, 2010], where the hippocampus generates simulated future scenarios to prepare for novel situations.

6. Theoretical Analysis

6.1 Data Efficiency

We argue that FMC achieves data efficiency through three complementary mechanisms. First, the tripartite memory system allows information to be stored once and retrieved many times, rather than requiring repeated exposure during training (the consolidation path from Episodic to Persistent memory implements a form of knowledge distillation [Hinton et al., 2015]). Second, the Imaginarium generates synthetic training signal that augments real data, effectively multiplying the dataset by a factor proportional to the acceptance rate of the VR.

Third, fractal growth means each expansion level inherits learned representations from the previous level, requiring only fine-tuning rather than training from scratch.

Let D be the original dataset size needed for a standard MoE, and let r be the VR acceptance rate. The effective dataset for FMC is:

$$D_{eff} = D_{real} + r \cdot D_{imagined} + \Sigma_k \, Transfer(F_{k-1} \rightarrow F_k)$$

Our hypothesis predicts $D_{real} \sim 0.4–0.6 \cdot D$ while maintaining equivalent performance, with the deficit compensated by the imagined and transferred components.

6.2 Emergent Generalization

The geometric cluster topology creates a natural mechanism for compositional generalization. When two previously unrelated clusters merge to handle a novel task, they combine representational subspaces in a way that can produce novel capabilities not explicitly trained. This is formalized as:

$$Capability(c_{ij}) \supseteq Capability(c_i) \cup Capability(c_j) \cup Emergent(c_i, c_j)$$

where $Emergent(c_i, c_j)$ represents novel capabilities arising from the interaction of previously isolated representational subspaces. This mirrors the cognitive science observation that novel creative solutions often arise from the combination of previously unrelated knowledge domains.

7. Proposed Experimental Protocol

We propose a three-phase evaluation to test FMC-H1:

Phase 1 — Controlled Scale (Proof of Concept): Train a 1B-parameter FMC model and a matched standard Switch MoE [Fedus et al., 2022] on FineWeb-Edu [Penedo et al., 2024]. Vary FMC's real data fraction from 40% to 100% while holding imagined data generation constant. Evaluate on standard benchmarks (MMLU, HellaSwag, ARC) and report the data-performance Pareto frontier.

Phase 2 — Cross-Domain Transfer: After Phase 1 training, evaluate on held-out domain-specific benchmarks (GSM8K for math, HumanEval for code, MedQA for medicine) without domain-specific fine-tuning. The hypothesis predicts FMC will show stronger zero-shot transfer due to emergent cluster merging.

Phase 3 — Distribution Shift Robustness: Evaluate on adversarially perturbed versions of the test benchmarks. The continuous self-verification loop should confer measurable robustness advantages detectable via calibration metrics (ECE, Brier score).

Ablation Schedule:

Ablation	Components Removed	Tests
FMC-full	None (full system)	All phases
FMC-noImag	Imaginarium + VR	Data efficiency (H1-i)
FMC-flat	Geometric clusters (revert to layers)	Transfer (H1-ii)
FMC-monoMem	Memory typing (all experts generic)	All sub-hypotheses
FMC-noFractal	Fractal growth (train full model directly)	Data efficiency (H1-i)

Table 2: *Ablation schedule for isolating the contribution of each FMC component.*

8. Discussion

8.1 Relationship to Neuroscience

FMC draws explicit parallels to known neural mechanisms. The tripartite memory system mirrors the hippocampal-neocortical-prefrontal triad. The Imaginarium parallels hippocampal preplay and the brain's ability to simulate future scenarios [Hassabis et al., 2007; Buckner, 2010]. The Verification Region loosely corresponds to the anterior cingulate cortex's role in conflict monitoring and error detection [Botvinick et al., 2004]. While these are analogies rather than direct implementations, they ground our architectural choices in a framework known to produce general intelligence.

8.2 Limitations and Risks

Several challenges must be addressed. **Communication overhead:** Asynchronous inter-agent messaging adds latency; efficient implementation may require custom CUDA kernels similar to DeepEP [Zhao et al., 2025]. **Hallucination control:** The VR acceptance threshold θ requires careful calibration—too permissive and false memories corrupt persistent knowledge; too strict and the Imaginarium provides no benefit. **Fractal depth:** The optimal number of expansion levels is unknown and may vary by task domain. **Evaluation:** Measuring 'emergent generalization' is inherently difficult and requires carefully designed held-out evaluations.

8.3 Broader Impact

If validated, FMC's data efficiency could democratize large model training by reducing the massive datasets currently required. However, the controlled hallucination mechanism raises safety concerns: a model that learns from its own imagined scenarios must be carefully constrained to prevent self-reinforcing biases. We recommend that any implementation include external ground-truth checkpoints at regular intervals during training.

9. Conclusion

We have presented the Fractal Memory-Cluster Architecture (FMC), a novel framework that reconceives Mixture-of-Experts through the lens of cognitive memory systems, geometric topology, and fractal self-similarity. Our comprehensive review of 2024–2026 literature confirms that while individual components have precedent, their synthesis into a unified architecture is genuinely novel. The formal hypothesis FMC-H1 makes specific, falsifiable predictions about data efficiency, cross-domain transfer, and robustness. We propose a rigorous experimental protocol with ablations to isolate the contribution of each innovation. FMC represents a principled step toward architectures that do not merely scale, but are organized according to the cognitive principles that underpin biological general intelligence.

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